CRA Charles River Associates

Form energy

Weathering the storm: Utility resource planning in the face of weather-driven reliability risks

March 2025

Executive summary

The electricity grid is facing unprecedented reliability risks due to weather, with utilities across the country experiencing heat waves, cold snaps, and other periods of prolonged grid stress. Weather-driven risks will only intensify in the coming years as electricity demand grows, aging generators are retired, and intermittent renewables continue supplying energy to the grid. In order for electric utilities to make strategic resource investments to mitigate these reliability risks, while ensuring affordability to customers, it is essential that their resource planning methods capture the fundamental dynamics of weather volatility. Such dynamics tend to be understated in traditional resource planning paradigms, which focus on "typical" weather conditions and overlook risk periods outside the system peak.

In this paper, Charles River Associates (CRA) and Form Energy share insights from a collaborative study that explores the impacts of weather volatility on resource planning optimization. We examined a utility case study that mirrors an industry-standard integrated resource planning analysis. The case study, based on a mid-sized electric utility in the Northwestern US, was developed with data inputs and modeling feedback from the utility's resource planning team. The analysis leveraged the unique modeling capabilities of CRA and Form Energy in their respective grid planning tools: Aurora[1] and Formware.[2]

We assessed how modeling different weather year scenarios in capacity expansion planning can impact resource investment decisions and the resulting cost and reliability of portfolios. We also examined how weather-driven risks can be mitigated by long-duration dispatchable resources[3]–a crucial class of resources that can be dispatched to meet the grid's reliability needs for several days at a time. The study considers a real utility system that is challenged with both significant load growth and a desire to diversify future investments beyond traditional thermal generation, reflecting the position of many utilities seeking to comply with state-level clean energy policies or manage regulatory, permitting, and fuel supply risks.

Key findings of the study include:

- Weather has a profound impact on portfolio needs, with total resource build varying by more than 40%, depending on the weather year used in optimization analysis.
- Clean, dispatchable resources insulate portfolios from weather-driven risks, improving reliability by more than 99%, regardless of the weather year used for planning.
- Clean, dispatchable resources reduce the cost of portfolios dramatically, by as much as 56% when portfolios are optimized over multiple weather years, relative to portfolios that only consider wind, solar, and short duration storage options.

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[1] Aurora is a commercially-available resource planning model, licensed by Energy Exemplar, that is commonly used by vertically-integrated utilities in North America for integrated resource planning.

[2] Formware is a capacity expansion and production cost model developed by Form Energy, which is designed to optimize grid investment and operational decisions with high fidelity representation of weather variability.

[3] This asset class includes a number of resources, including a variety of clean dispatchable resources such as multi-day energy storage technologies, small modular nuclear reactors, green hydrogen, and geothermal systems.

This paper identifies approaches that enable utilities to design more reliable and cost-effective portfolios in the face of weather volatility. Specifically, we recommend including multiple weather years within capacity expansion planning and including clean, multi-day technologies as resource candidates within planning exercises. These practices will help utility resource planners to more critically examine whether their existing practices adequately capture the role of weather and will provide for a more stable and cost-effective grid in a future where weather-driven impacts represent an increasing threat.

Introduction

Now, more than ever before, weather has a profound impact on the power system. The grid is increasingly vulnerable to weather-driven reliability risks across all regions of the United States, from winter storms and summer heat waves to prolonged renewable lulls. These multi-day periods of grid stress have challenged electric grid operators over the last several years and will only become more severe due to rapid load growth, retirement of aging generators, and continued supply from intermittent renewable resources.

The most impactful recent example is Winter Storm Uri, an extreme winter weather event affecting Texas and the South-Central United States from February 8th - 20th, 2021. Due to record amounts of snow and cold temperatures, the Electric Reliability Council of Texas (ERCOT) lost an average of 34,000 MW generation for two consecutive days, equal to almost half of the peak electric load of 69,871 MW during the period.[4] ERCOT was forced to implement rolling blackouts that affected 4.5 million Texas customers and resulted in damages of $80 billion - $130 billion.[5] Since then, other multi-day cold weather events across the country have led to grid reliability challenges and skyrocketing wholesale market prices.[6] Summer heat waves can have similar reliability impacts, as seen in the August 2020 rolling blackouts in California, when a late afternoon power demand surge from high temperatures coincided with declining solar output.[7]

Looking forward, system resource planners must better represent the uncertainty and volatility of weather as they determine which resources are needed to reliably serve electricity demand across all hours of the year. Current industry standard approaches to capacity expansion planning[8] largely oversimplify the role of weather-driven phenomena in three ways:

1. Capacity expansion exercises usually rely on a "typical" meteorological year. This is a representative weather scenario which aggregates commonly observed weather patterns but often fails to adequately represent the full spectrum of weather and its extremes.

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[4] The February 2021 Cold Weather Outages in Texas and the South Central United States. November 2021. Federal Energy Regulatory Commission (FERC), North American Electric Reliability Corporations (NERC), and Regional Entities.

[5] Id.

[6] See “Powerex. 2024. Analysis of the January 2024 Winter Weather Event.” See also “ISO Newswire. 2023. ISO-NE maintains system reliability through generator outages, loss of imports on Christmas Eve.”

[7] Storrow, Benjamin. 2024. What heat wave? Batteries keep the lights on in California. E&E News.

[8] Capacity expansion refers to a class of planning models used to identify the least-cost set of investments for a grid planner, subject to reliability, emissions, and other constraints. Capacity expansion models are distinct from other grid planning tools such as production cost or resource adequacy models, which do not optimize least-cost investments.

2. Conventional capacity expansion tools often employ “time sampling” techniques, which optimize resource investments by simulating a series of representative days or weeks, rather than including all 8,760 hours of the year. This simplification reduces the computational requirements of the model but overlooks critical reliability challenges and resource interactions that can occur outside of the representative periods.
3. Standard resource adequacy frameworks, while intended to account for weather uncertainty, often oversimplify the interactive dynamics between resources like renewables and storage, while failing to properly reflect the outsized impact of extreme weather events.

As a result, resource planners may arrive at portfolios that are either cost-inefficient or fall short of meeting reliability standards across a realistic range of weather scenarios. Future grids will require more sophisticated approaches to planning for weather variability.

By updating model methodologies to more accurately represent weather volatility, resource planners can better optimize their portfolios to deliver reliable service across a variety of weather conditions, at the lowest possible cost to customers. Such resource planning approaches could surface needs for new, innovative grid resources. This is especially true as utilities look for new options to navigate a broad set of strategic risks, such as permitting and regulatory uncertainty, compliance with state-level clean energy goals or policies, commodity and fuel price risks, and supply chain challenges.

Clean, dispatchable resources are a promising solution to address weather-driven reliability risks on the grid. This resource class refers to non-emitting technologies that can be dispatched to meet the grid’s reliability needs for several days at a time. A number of clean, dispatchable resources are being commercialized today, including multi-day energy storage technologies (e.g. iron-air batteries), small modular nuclear reactors, green hydrogen, and geothermal systems.

This study investigates the impact of weather-driven grid dynamics on the outcomes of resource planning optimization, and the corresponding role of the aforementioned clean, dispatchable resources. We explore these dynamics in the context of a utility resource planning case study to understand how weather volatility ultimately shapes portfolio investment decisions, costs, and reliability.

Methods

This paper examines a real-world utility resource planning case study to explore various modeling choices related to weather-driven volatility. This case study is based on a mid-sized electric utility system in the Northwestern US and was developed with data inputs and modeling feedback from the utility’s resource planning team. The case study is intended to represent a typical integrated resource planning exercise by reflecting the scale, complexity, and computational limitations of many typical utility resource planning models.

The analysis was performed in a collaboration between Charles River Associates (CRA) and Form Energy. CRA performed long-term capacity expansion modeling in Aurora,[9] determining least-cost portfolios optimized under various weather scenarios and technology configurations. Form Energy then used Formware to perform additional capacity expansion modeling, as well as production cost simulation on all portfolios to quantify their cost and reliability. The Formware analysis leveraged the model's unique capabilities to optimize resource investment decisions across a range of weather year scenarios, a feature known as multi-weather year co-optimization.

We started by developing a long-term capacity expansion (LTCE) model of the utility's portfolio in Aurora to determine least-cost investment decisions across a 20-year planning horizon (2024-2043). We aligned the vast majority of inputs to the utility's last published Integrated Resource Plan, including (i) candidate resource cost and technology specs, (ii) forecasted load growth, and (iii) resource adequacy assumptions–namely, seasonal planning reserve margins and effective load carrying capacities. This study only considered the utility's reference case assumptions; in practice, IRP's often must consider various sensitivities related to various policy and market conditions.

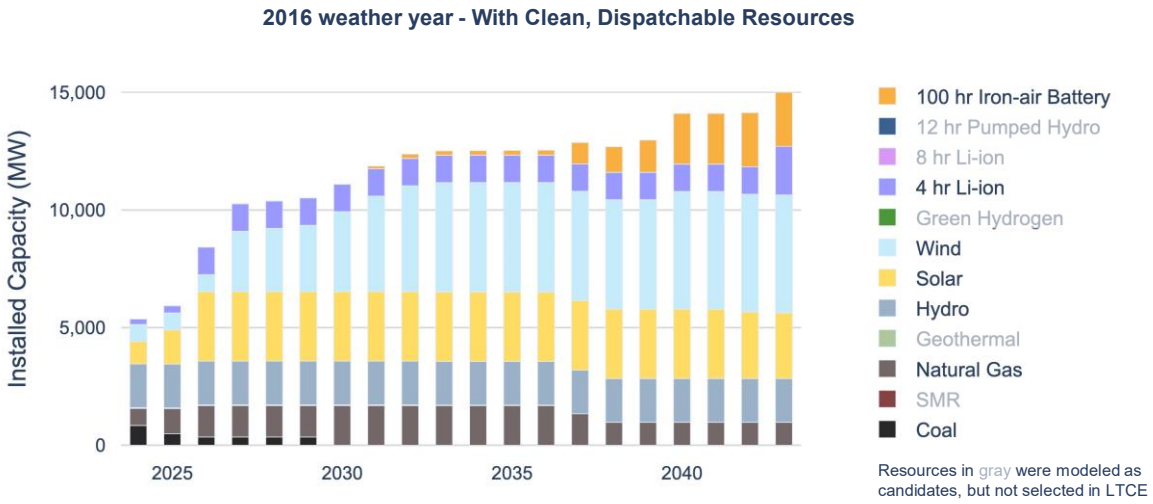
The portfolio capacities of thermal resources were aligned directly with the utility's IRP Preferred Portfolio, rather than optimized within the LTCE model. The utility's resource plan includes some thermal conversions but does not bring additional thermal capacity online after 2026. This is driven by the utility's desire to manage a broad set of strategic risks, such as compliance with clean energy goals or policies, commodity and fuel price risks, and supply chain uncertainty. In line with the IRP, the analysis compares portfolios with new build options consisting of wind, solar, and short duration storage options against portfolios which additionally include clean, dispatchable technologies.

To quantify the impact of weather volatility on resource planning outcomes, we examined the results of LTCE modeling across various weather years. We first developed 35 distinct weather year scenarios for the study, each consisting of hourly renewable and load profile shapes that are correlated to a given year of historical meteorological data. We then ran the LTCE in Aurora on five of these weather year scenarios (2013, 2015, 2016, 2017, 2019).[10] Remaining weather scenarios were used in the production cost simulation, described later within the Methods section. This LTCE modeling resulted in a unique portfolio expansion plan for each of the five weather years. Figure 1 provides an example portfolio expansion plan from the LTCE modeling. We ran each of these LTCE simulations in Aurora with an 8760-hour chronology to capture sequential variation in weather across all hours of the year.

[9] Aurora is a commercially-available resource planning model, licensed by Energy Exemplar, that is commonly used by vertically-integrated utilities in North America for integrated resource planning.

[10] We chose these five weather year scenarios to capture a wide distribution of weather conditions, based on criteria such as severity of high net load events (periods of high demand and low renewable output).

Figure 1: Example least-cost portfolio expansion plan from Aurora LTCE



In addition, we evaluated the same weather year scenarios in Formware[11] using a novel LTCE approach known as multi-weather year co-optimization. This approach determines a single portfolio expansion plan that is simultaneously optimized to be least-cost across all input weather year scenarios, while satisfying system constraints (e.g. planning reserve margins, power balance constraints, etc.). This approach can help design portfolios that are least-cost and reliable across a wide array of weather conditions.

We also assessed the role of clean, dispatchable resources in managing weather volatility. This resource class refers to assets which can be dispatched for multiple days at a time, thus helping to maintain reliable grid operations during prolonged episodes of weather-driven grid stress. In this study, four technologies were considered within this category, in line with the utility's 2023 IRP:

1. 100-hour iron-air batteries
2. Small modular reactors
3. Green hydrogen
4. Geothermal

We performed the LTCE with and without these clean, dispatchable resources as candidates for selection, to assess their impact on portfolio outcomes.[12]

We ran the resulting LTCE portfolios through a production cost simulation in Formware, across all 35 weather scenarios to evaluate portfolio cost and reliability. The portfolio cost is inclusive of all

[11] Formware is a capacity expansion and production cost model developed by Form Energy, which is designed to optimize grid investment and operational decisions with high fidelity representation of weather variability.

[12] While four types of clean, dispatchable resources were included in the LTCE modeling, neither green hydrogen nor small modular reactors were selected in any of the portfolios. The specific set of technologies selected by least-cost capacity expansion depends on a number of modeling factors, including technology cost, performance assumptions, and system conditions.

resource capex, operating costs, and tax credits13 based on the assumptions in the utility's IRP. We quantified the reliability risk in terms of "Expected Unserved Energy" (EUE), which represents the average fraction of annual energy consumption that was unserved (that is, loss of load) across all 35 weather scenarios.

Further details on the study methodology can be found in Appendix A. Candidate resource assumptions are provided in Appendix C.

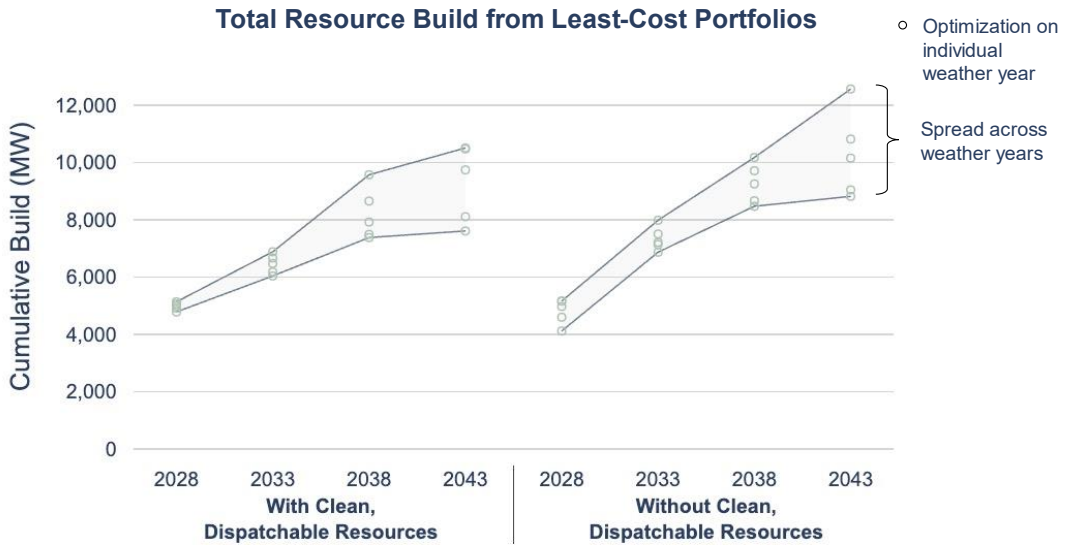
Findings

From our analysis, we identified four key insights:

Weather has a profound impact on portfolio needs, with total resource build varying by more than 40% depending on the weather year used in planning optimization.

Total resource build in the least-cost portfolio can vary significantly as a function of the weather year used in the LTCE model. For instance, in portfolios without clean, dispatchable resources, there is a 42% difference between minimum and maximum resource build across the five weather years (cumulative additions by 2043). This difference is illustrated in Figure 2, which displays the results of long-term capacity expansion in Aurora, performed on five distinct weather year scenarios.

Figure 2: Total resource build optimized on five distinct weather years



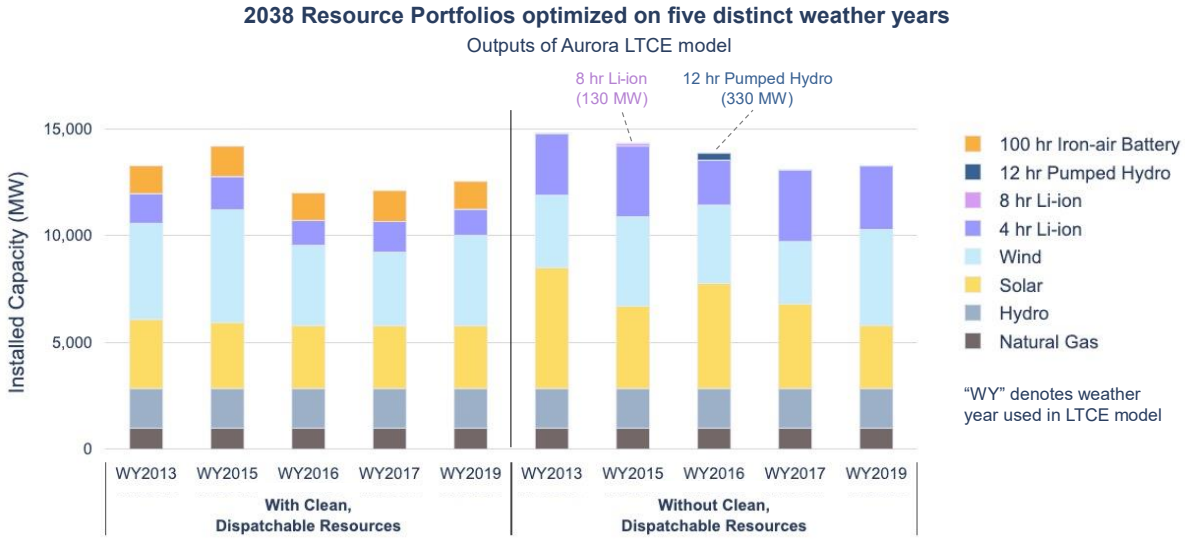
Results of long-term capacity expansion in Aurora over 20 -year planning horizon

[13] Tax credit considers both, Investment Tax Credit (ITC) and Production Tax Credit (PTC).

Total build increases in the absence of clean, dispatchable resources, as observed in the comparison between the two sides of Figure 2; the magnitude of this increase depends on the weather year, ranging from 3% to 20% in the 2043 portfolios. The overall sensitivity of resource build to choice of weather year grows over time, as the system's reliability needs are increasingly impacted by weather conditions.

The resource composition of the least-cost portfolio also heavily depends upon the weather year used in LTCE modeling. Figure 3 illustrates these important differences between portfolios; it displays the 2038 portfolios resulting from capacity expansion on five distinct weather year scenarios, with and without clean, dispatchable resources. The selection of renewable resources varies depending on the weather year, both in terms of total buildout and the relative mix of solar and wind. The optimal storage mix also varies based on the weather year used. This variation is relatively muted when clean, dispatchable resources are available: all portfolios select 4-hour Li-ion and 100-hour iron-air in roughly equal amounts, with overall storage build ranging from 2.1-2.6 GW. Yet, in the absence of clean, dispatchable resources, storage buildout is more sensitive to weather year. Overall storage build ranges from 2.1-3.1 GW across weather years, which is double the spread compared to the portfolios with clean, dispatchable resources. There is also much greater variation in the types of storage resources selected, depending on the weather year. Some weather years only select 4-hour Li-ion storage, while other weather years identify needs for 8-12-hour storage (WY2015 and WY2016) in the least-cost portfolio.

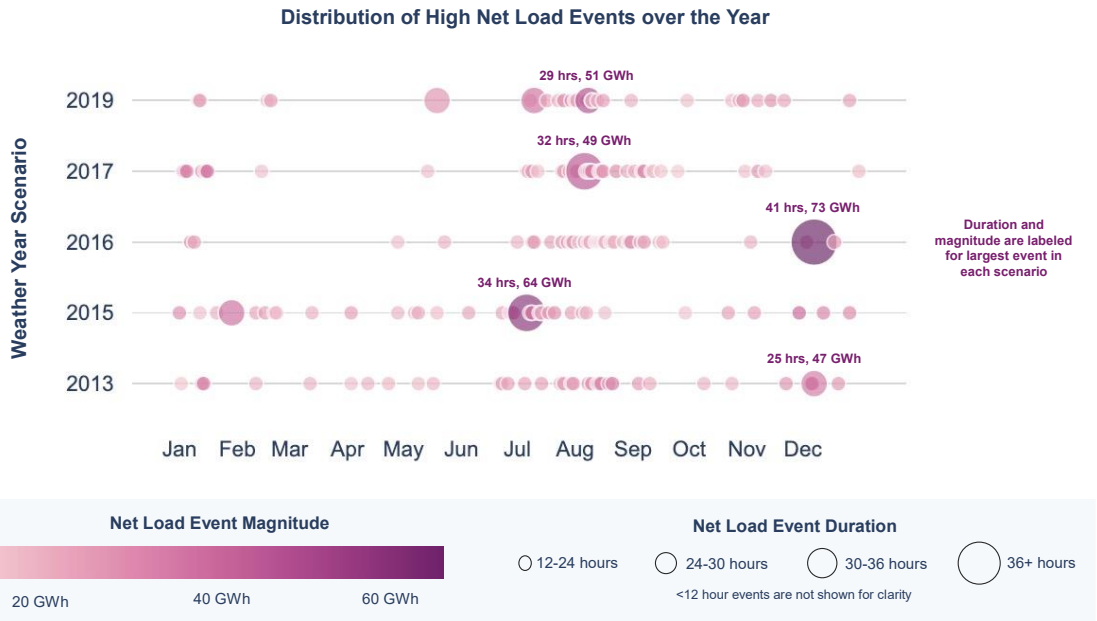
Figure 3: Least-cost resource portfolios optimized on five distinct weather years



The dynamics of net load are an important driver of these varying resource build outcomes across weather years. Net load describes the difference between total load and renewable generation–in other words, the load in any given hour which must be served by non-intermittent resources. Net load is highly dependent on the weather scenario, as it is a function of both load (correlated with temperature) and renewable generation (correlated with solar irradiance and wind speed). The specific pattern of net load can vary dramatically between weather scenarios, as illustrated in

Figure 4, which shows the distribution of 2038 high net load events[14] across different weather years. The magnitude, duration, and sequencing of these events changes substantially across weather years, which ultimately impacts the portfolio of resources that is required to maintain reliability. The seasonality of net load also differs between weather years, with some showing a greater concentration of reliability risk in the winter than others. Performing capacity expansion across several weather year scenarios, with an 8760 chronology,[15] thus enables resource planners to capture portfolio reliability needs across a range of net load conditions.

Figure 4: Distribution of 2038 high net load events (top 20% of net load) across weather years



The optimal mix of storage resources is particularly sensitive to the pattern of net load events in a given weather year. Longer duration, higher magnitude events tend to surface a greater need for longer duration storage resources. This is consistent with what we see in Figures 3 and 4; the two weather years with the longest duration and highest magnitude events, 2015 and 2016, are also the only two weather years which select 8-12-hour storage investments (in portfolios without clean, dispatchable resources). The specific sequencing of events matters as well. Storage must have enough energy to discharge during high net load events; the closer together these events are, the more challenging this will be for shorter duration batteries that require frequent recharging. For instance, a 4-hour battery may be able to deliver energy for a single afternoon with high peak net load. However, if the next several days present low solar output and high afternoon loads, grid operators may be unable to fully recharge and discharge 4-hour batteries for several consecutive days. In contrast, multi-day storage assets can be discharged for days at a time without

[14] Refers to continuous periods in which net load is in the top 20th percentile across all 5 weather years. The net load metrics displayed in Figure 4 are based on the 2038 "With clean, dispatchable resources" portfolios shown in Figure 3.

[15] LTCE model was run with 8760-hour chronology to capture weather-driven volatility in load and renewables across the entire year

recharging, making them more reliable in the face of back-to-back net load events. This suggests that the degree to which different storage types are selected in a least-cost portfolio can depend heavily upon the net load dynamics in the modeled weather year scenario.

In contrast to net load, changes in *peak load* are likely not a major contributor to the observed variance in resource build across weather years. For example, the two weather year scenarios with the greatest spread in 2043 cumulative resource build (2016 and 2017) show a 42% difference in resource build but only have a 2% difference in annual peak and 6% difference in winter peak. These same two weather year scenarios show a much greater disparity in net load; Figure 4 shows that the largest net load event in the 2016 weather scenario has a 49% higher magnitude than that of the 2017 weather scenario. These findings suggest that peak load alone is not a strong indicator of capacity needs, and that, although utilities usually plan for a forecasted peak that is weather-normalized, net load is a much more salient factor for reliability planning. Capturing weather-driven reliability risks, therefore, requires granular modeling of year-round net load conditions.

Clean, dispatchable resources insulate portfolios from weather-driven risks, improving reliability by more than 99% regardless of the weather year used for planning.

Figure 5 presents the reliability and cost of the portfolios that were derived from five different weather year scenarios. We performed this assessment by running a production cost simulation on the portfolios resulting from Aurora LTCE modeling (shown in Figure 3) across 35 weather year scenarios. The reliability risk is quantified in terms of expected unserved energy (EUE) and represents the average loss of load across the 35 scenarios as a fraction of total demand. The portfolio cost represents the amortized capital costs and annual operating costs of all resources within the portfolio, inclusive of Investment Tax Credit (ITC) and Production Tax Credit (PTC) benefits.

Figure 5: Reliability and cost of portfolios from Aurora LTCE on various weather years

When comparing portfolios with and without clean, dispatchable resources, we observe stark differences in reliability risk. In the absence of multi-day storage, the portfolio EUE is in the range of 0.02-0.05%, more than an order of magnitude less reliable than typical EUE standards of 0.002%.[16] In contrast, we see substantial reliability improvements when clean, dispatchable resources, such as 100-hour iron-air batteries, are included in capacity expansion planning. Including multi-day storage in these portfolios reduces EUE by more than 99%, bringing all portfolios to a level of reliability risk well below typical EUE standards.[17]

We also find that the reliability outcomes of capacity expansion planning are highly sensitive to the specific choice of weather year when clean, dispatchable resources are not included as candidate resources. For example, in the cases without these resources, the WY2017 portfolio has a 3x higher EUE as compared to the WY2015 portfolio. These reliability differences are driven by the composition of resource portfolios shown in Figure 3, with more reliable portfolios including greater total resource build (WY2015) as well as longer-duration storage resources (WY2015 and WY2016).

In contrast, portfolios with clean, dispatchable resources meet reliability standards regardless of the weather year modeled within the optimization. This helps derisk capacity expansion planning from a reliability perspective, reducing the sensitivity of reliability outcomes to a specific choice of weather year. Simultaneously, the inclusion of clean, dispatchable resources enable reliability needs to be served at a lower cost; across the five weather scenarios, the portfolios with clean, multi-day storage resources are 15-25% cheaper than those without. These cost savings are primarily driven by avoided resource build. By delivering firm capacity to the portfolio, clean, dispatchable resources avoid overbuild of short-duration storage and renewables that would otherwise be needed to maintain reliability. Additional detail on the breakdown of portfolio cost is provided in Appendix B.

Hourly operations of portfolios provide further insight into how multi-day resources reduce exposure of portfolios to weather-driven reliability risks. Figure 6 displays simulated portfolio operations during a winter cold snap in the 1983 weather year scenario. During this week, the coupling of high heating loads and low wind generation results in several consecutive days of severe grid stress. The left panel shows that when multi-day storage is part of the portfolio, it provides a low-cost reservoir of energy that can be discharged for multiple days at a time without requiring recharge. The stored energy reserves from multi-day storage provide a hedge against weather volatility, delivering on-demand energy throughout the five days of critical reliability needs. In the absence of multi-day storage, the system has access to a much smaller reservoir of stored energy, as seen in the stored energy plot on the bottom right. Compared to the portfolio with multi-day storage, the system without it has access to 85% less energy reserves, due to the limited duration of 4-hour Li-ion. In

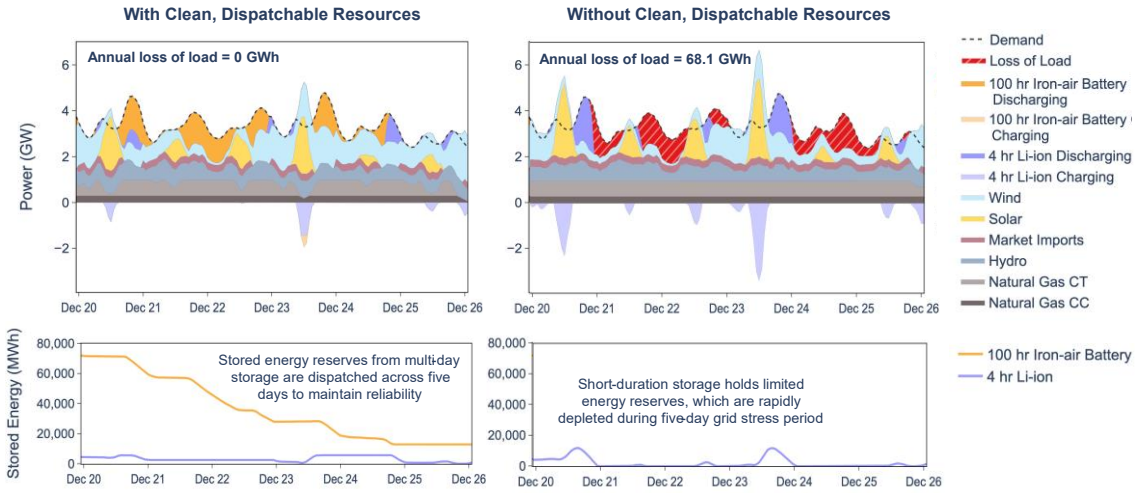
[16] This typical EUE standard refers to the 0.002% EUE standard used by the Australian Energy Market Operator (AEMO) in system planning (see pg. 38 of 2024 ISP). In recent years, several markets have adopted EUE as a core reliability metric, with AEMO being the largest. This move towards EUE is intended to capture the magnitude of loss of load events with more granularity than LOLE.

[17] It should be noted that the EUE metrics reported in this study only reflect loss of load across different weather scenarios. Typically, calculation of EUE would reflect additional grid contingency scenarios such as thermal outages and transmission outages, which are not accounted for here.

the portfolio without multi-day storage, these reserves are rapidly depleted less than 24 hours into the grid stress period, ultimately resulting in 68 GWh of unserved energy.

Figure 6: Portfolio operations during severe winter conditions

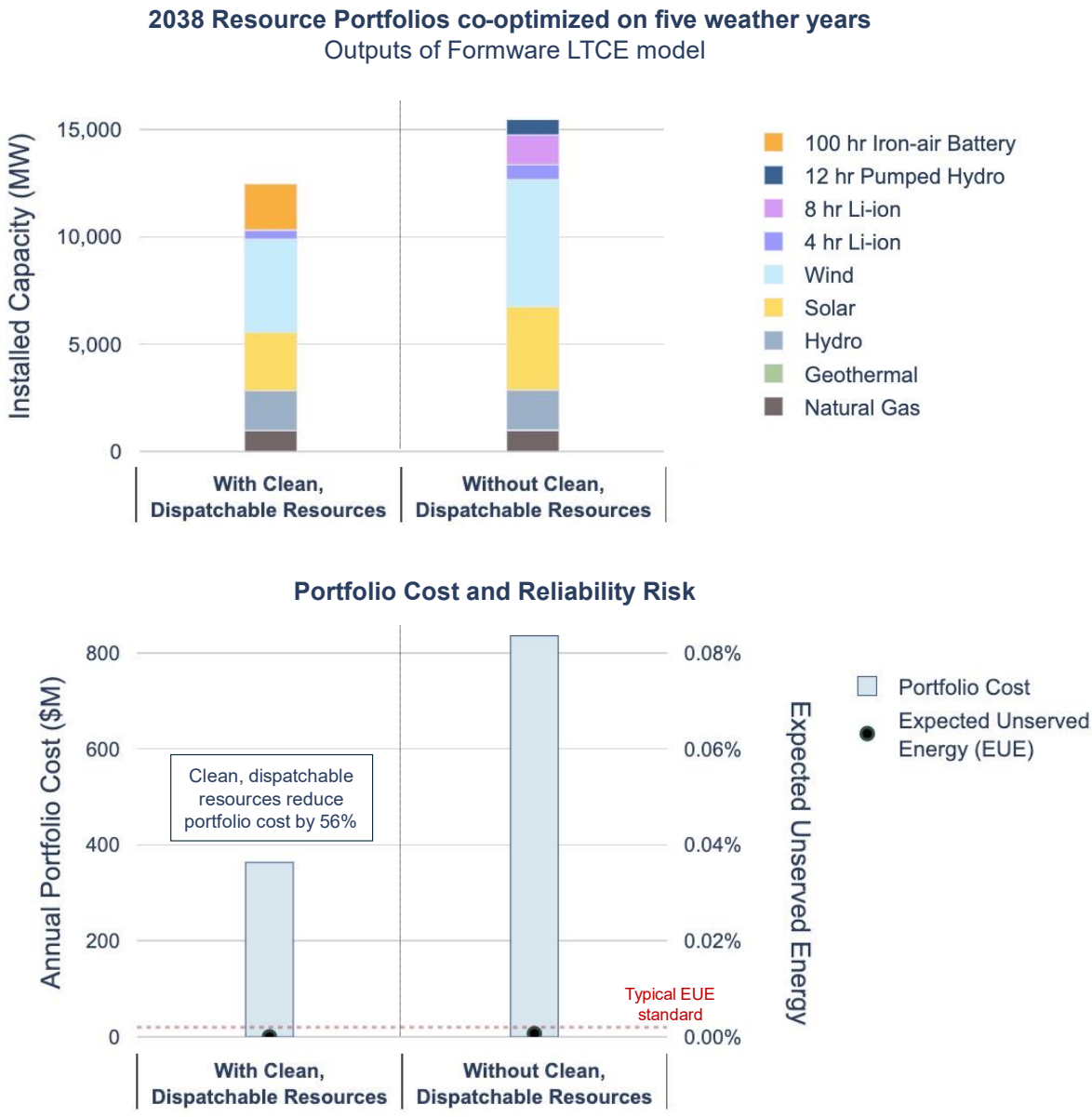
(Portfolios determined via Aurora LTCE on 2017 weather year, dispatched against 1983 weather year)



Clean, dispatchable resources reduce the cost of portfolios dramatically, by as much as 56% when portfolios are optimized over multiple weather years.

Clean, dispatchable resources play a critical role in identifying portfolios that are both least-cost and reliable across a wide array of weather conditions. As previously discussed, the Aurora LTCE portfolios in Figure 5 show that clean, dispatchable resources simultaneously improve portfolio reliability, while reducing cost by 15-25% across the five weather year scenarios. These cost savings, however, are even more apparent when, focusing on a single year in the future, portfolios are optimized across multiple years of weather data at once. Figure 7 displays the portfolios for the year 2038, resulting from multi-weather year co-optimization in Formware. This capacity expansion methodology optimizes resource build simultaneously across five weather year scenarios to produce a single least-cost expansion plan. Unlike the LTCE results presented in Figure 5, both the portfolios with and without clean, dispatchable resources meet the typical EUE planning standard. However, in designing the portfolios to achieve the same level of reliability, we find that the portfolio with clean, dispatchable resources is now 56% lower in cost. The cost savings are primarily driven by avoided resource build–by selecting 2.1 GW of 100-hour iron-air batteries, the portfolio avoids 3 GW of total resource build (renewables, 8-hour Li-ion, and 12-hour pumped hydro). Without clean, dispatchable resources, more resource build is required to serve the variety of grid stress conditions presented in the five modeled weather year scenarios. A more detailed breakdown of portfolio costs is provided in Appendix B.

Figure 7: Portfolio capacity, cost, and reliability from multi-weather year co-optimization



The use of multiple weather years in long-term capacity expansion planning can help identify more reliable and cost-effective portfolios.

A single weather year of operational data does not provide enough information to identify the most reliable and cost-effective portfolio of resources. More weather data is needed, especially as weather has a growing impact on the reliability of the electricity system via electrified load and

renewable generation. Capturing the range in weather conditions across multiple years is critical to identify the type of risk periods faced by grids, as well as the most appropriate and cost-effective resource mix to address that risk.

Some weather years are more challenging to reliably supply than others, as indicated by the range in resources needed across different weather years shown in Figures 2 and 3. However, it is challenging to predict in advance which weather years will require more resources to meet reliability standards, because the challenges associated with particular weather conditions depend on the underlying portfolio. For example, planned renewable investments affect what conditions may lead to low generation; a windy, cloudy cold snap may be a challenge in a solar-heavy system but a non-issue in a wind-heavy system. Storage resources add another dimension of complexity to reliability planning, as the sequence of weather conditions has a greater impact on reliability--for example, whether there is enough solar generation to charge short-duration batteries during the day before a peak evening net load event, especially if those batteries were discharged the previous evening. Capturing the range of outcomes for weather sequencing requires more weather years.

The traditional approach to incorporating weather risks in resource planning involves the use of a Planning Reserve Margin (PRM)[18] coupled with Effective Load Carrying Capacity (ELCC)[19] assumptions for each resource. However, this approach does not fully capture the growing impact of weather volatility on portfolio reliability. There are two main reasons for this shortfall.

First, PRM-based frameworks are most often based on LOLE (Loss of Load Expectation), which does not capture the severity of a potential loss of load event, only its occurrence. Weather-driven effects, especially severe weather, can lead to a large variation in the severity of loss of load events. This effect is evident in Figure 5, showing that despite the use of the same LOLE-based PRM/ELCC values in Aurora to generate the portfolios, there is a large variation in portfolio risk when measured in terms of Expected Unserved Energy (EUE), which captures the severity of loss of load events.

Second, a PRM-based framework will not capture the interaction between weather and portfolio selection that drives the reliability risk in future grids. The calculation of PRM and ELCC inputs is typically done with many years of weather data, but only considers a narrow subset of all possible resource portfolios due to computational limitations. This approach vastly understates the impact of portfolio composition on reliability risk across different weather conditions, which is especially important in grids with a high level of renewables and storage.

Using multiple weather years in long-term capacity expansion enables resource planners to capture the interaction of weather and portfolio effects, which will help identify the most reliable and cost-effective portfolios. This approach is critical for capturing grid reliability during infrequent, but challenging, weather events. Widely used resource accreditation techniques, like ELCC, only

[18] PRM is a resource adequacy metric that indicates the total “perfect capacity” required to maintain reliability on a power system across a variety of grid contingencies. Typically, it is a static value applied to the entire year but can also be differentiated by season.

[19] ELCC is a resource adequacy metric that indicates the equivalent “perfect capacity” delivered by an individual resource, or sometimes by a combination of two or more resources.

provide information about the average performance of resources, and, for example, may indicate that solar plus short-duration storage is highly available and will support reliability in sufficient quantities. However, these averages are of little use during rare-but-predictable cloudy, high-load days. Capturing these scenarios directly in capacity planning, holds the potential to identify more reliable and cost-effective portfolios.

Resource planners can address this reliability planning challenge by using multiple weather years in their system planning studies. This additional weather data will ensure that weather-driven reliability risks are captured appropriately, incorporating that data as either multiple scenarios, or by planning for all weather years simultaneously, through multi-weather-year joint optimization. In the first option, modeling will generate multiple portfolios, as illustrated in Figure 5; planners can then test the reliability of each generated portfolio to identify the most reliable and cost-effective plan. Even without subsequent reliability testing, planners can use the portfolios requiring higher resource investments to guide reliability-focused investments.

The second option for integrating multiple weather years, is to jointly plan for all weather years at once, via multi-investment year co-optimization. The portfolios resulting from this approach, as described in Figure 7, are designed to meet year-round reliability requirements across all modeled weather years simultaneously. Portfolios generated in this way demonstrate greater reliability than those based on a single weather year, even the weather year with the greatest capacity needs. This is because each weather year presents unique reliability challenges that vary across different times of the year and under different portfolio resource mixes.

Conclusions

The results of this study illustrate that weather dynamics play a pivotal role in resource planning. The weather conditions modeled within a resource planning optimization have major implications on resource investment decisions, and the resulting cost and reliability of portfolios. Including clean, dispatchable resources within resource planning exercises can mitigate weather-driven reliability risks, identifying which portfolios are more cost-effective and reliable across a range of weather. Given these findings, resource planning best practices should: 1) optimize resource portfolios around multiple weather years; and 2) include clean, multi-day technologies as candidate resources in capacity optimization.

Planners should optimize resource portfolios using multiple weather years, to consider the realistic spread in resource needs across varied weather conditions.

A single weather year of operational data does not provide enough information to identify the most reliable and cost-effective portfolio of resources. Recent winter and summer weather events across the United States have demonstrated that portfolios developed and built using a typical weather year can and do underperform during periods of grid stress, resulting in greater reliance on high-priced electricity imports in the best case, and emergency conditions with rolling blackouts in the worst case. Thus, it is critical to capture the range in weather conditions across multiple

years as a routine part of the resource planning process to identify the type of risk periods faced by grids, as well as the most appropriate and cost-effective resource mix to address that risk.

Resource planners should account for weather variability in their modeling process by evaluating multiple weather year scenarios within capacity expansion planning. Although running multiple weather year scenarios adds additional scope to resource planning exercises, this approach can pay dividends by identifying the resources that are required for maintaining reliability across a breadth of weather conditions. The portfolios resulting from the various weather year scenarios can then be tested to select which, most closely, matches resource planning goals, in terms of both cost and reliability.

As planning tools evolve, the ability to co-optimize resource portfolios across multiple weather years will become a more common resource planning practice. This approach will identify a single, least-cost portfolio expansion plan, designed to meet reliability requirements across a range of weather scenarios, at the lowest possible cost.

Resource planners should include clean, dispatchable resources in capacity expansion modeling, to arrive at portfolios that may be cheaper and more reliable across a range of weather conditions.

Clean, dispatchable resources refer to a class of non-emitting technologies that can be dispatched for multiple days at a time, including small modular nuclear reactors, advanced geothermal, and 100-hour iron-air batteries. In this analysis, the model selects these clean, dispatchable resources to provide cost-effective, reliability capacity across a range of different weather conditions. These resources are particularly valuable during periods of severe net load events; and thus, are selected in higher quantities in these particular weather years. In this analysis, we find that multi-day storage resources improve portfolio reliability by >99%, while also reducing total cost by up to 56% when the model selects them in a least-cost optimization.

To realize these cost and reliability benefits in their own system portfolios, resource planners should include clean, multi-day technologies as resource candidates for their least-cost optimization models. Clean, dispatchable resources provide both reliability and resiliency value to the grid, while lowering the total resource build needed to meet demand across different weather years. Cost savings are driven by avoided resource build, as portfolios without clean, dispatchable resources require additional investment in renewables and shorter-duration forms of storage to reliably meet electric demand. Thus, including clean, dispatchable resources in IRP studies will help position utilities to maintain reliability at a lower cost, no matter the weather.

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Charles River Associates is a leading global consulting firm that offers strategic, economic, and financial expertise to major corporations and other businesses around the world. CRA's Energy Practice provides services to a wide range of industry clients, including utilities, ISOs, RTOs, large customers, and investors. The Energy Practice has offices in Boston, New York City, Washington DC, Toronto, London, Houston, Los Angeles, Salt Lake City, Dusseldorf, and Munich. Learn more at **www.crai.com/energy**.

About Form Energy

Form Energy, Inc. is a U.S. energy storage technology and manufacturing company that is commercializing a rechargeable, iron-air battery for the electricity grid that is capable of discharging for 100 hours at a time. With a system cost less than 1/10th the cost of lithium-ion battery technology, Form's multi-day storage solution will enable a clean electric grid that is reliable and cost-effective year-round. Form has a high-volume manufacturing facility in Weirton, WV, as well as facilities in Somerville, MA and the San Francisco Bay Area. Learn more at **www.formenergy.com**.

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Appendix A: Modeling inputs and methods

Model inputs

The study's resource planning models in both Aurora and Formware were primarily constructed using inputs and assumptions consistent with the utility's last-released IRP. These include the following:

- All candidate resource options with associated technical specs
- Capital and operating cost assumptions for all candidate resources
- Existing supply-side resources. All individual thermal and renewable generators were modeled, with generator specific attributes (heat rate, VOM, etc.)
- Planned schedule of thermal builds, conversions, and retirements from outputs of the utility's 2023 IRP. Given that a variety of factors influence thermal build and retirement decisions, this schedule was input directly as reported in the IRP output, rather than decided endogenously within the LTCE
- Forecasted annual load and annual energy consumption
- Resource adequacy assumptions (seasonal planning reserve margin and resource accreditation)
- Availability and hourly price of regional market imports
- Fuel price projections
- ITC and PTC assumptions
- Carbon price
- Carbon emission constraints were applied within the LTCE to align portfolios with the reported emissions output of the utility's 2023 IRP preferred portfolio

It should be noted that green hydrogen was modeled as an energy storage resource, consisting of an electrolyzer, geologic storage, and a hydrogen-ready combustion turbine. This representation within the model accounts for the realistic constraints associated with production, storage, and consumption of green hydrogen.

Detailed cost and technology performance assumptions for candidate resources are provided in Appendix C.

Generating weather year scenarios

The study utilized 35 weather year scenarios, reflecting historical meteorological data. Each weather year scenario consists of the following 8760-hour profiles:

- Solar and wind profiles: profiles were generated for 6 different geographical zones for solar resources, and 8 different geographical zones for wind resources. Solar and wind capacity

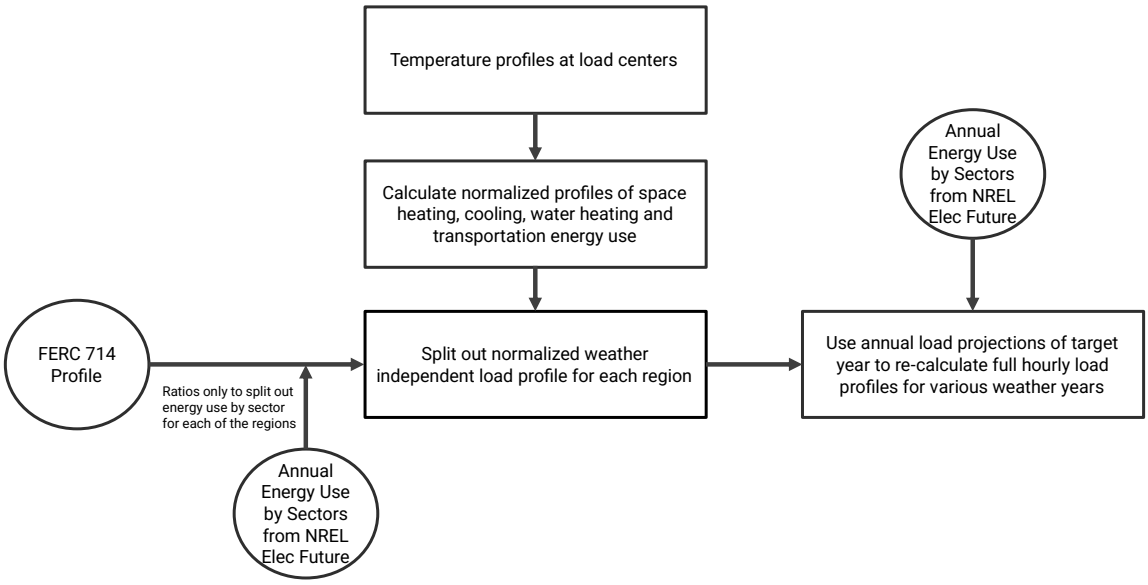
factors were sourced from Pfenninger and Staffell[20, 21] based on the NASA MERRA reanalysis and CM-SAF SARA H datasets.

- Hydroelectric generation profiles: historical generation data for the utility's hydroelectric assets in years 2013-2022. The median hydro generation year was used in weather year scenarios outside of 2013-2022.
- Load profiles: profiles were shaped to reflect correlations between load and hourly temperature data. Unique load profiles were derived for the 20 investment years in the study period (2024-2043), reflecting forecasted load growth and changes in electricity end uses. The methodology for generating temperature-correlated hourly load profiles is described in the following section.

Hourly load profiles

To model the impact of weather on load with high degree of fidelity, the load is split into two categories: (1) weather dependent loads and (2) weather independent loads. The weather dependent loads include space and water heating, space cooling and electric transport. Weather independent loads include industrial processes, military use, cooking, washing, and lighting, among others. The profiles of weather dependent loads change with the weather year used in the modeling, while the weather independent loads are assumed to remain unchanged.

Figure A1: Process diagram for creation of weather correlated load profiles



[20] Pfenninger, Stefan and Staffell, Iain (2016). Long-term patterns of European PV output using 30 years of validated hourly reanalysis and satellite data. Energy 114, pp. 1251-1265. doi: 10.1016/j.energy.2016.08.060

[21] Staffell, Iain and Pfenninger, Stefan (2016). Using Bias-Corrected Reanalysis to Simulate Current and Future Wind Power Output. Energy 114, pp. 1224-1239. doi: 10.1016/j.energy.2016.08.068

Figure A1 shows the process diagram used to create the load profiles in this study. The 2017 load profile for the various balancing areas from FERC Form 714 was used as a starting point. The NREL electrification futures study was used to determine the ratio of the annual energy consumption that came from weather dependent loads and weather independent loads. The normalized hourly profiles for weather dependent loads were created using temperature profiles from 2017 (to match the FERC load data) at the load centers for the regions modeled. The method used to calculate the normalized load shapes for the weather driven loads is very similar to the one described in Section 2.5 of Vibrant Clean Energy's WIS:dom-P model.[22] Hourly historical temperature data used to calculate normalized load shapes were sourced from Pfenninger and Staffell. Once the hourly profiles for weather dependent loads were created, the normalized weather independent load profile could be calculated by subtracting the weather dependent load profile from the FERC Form 714 load profile.

Load profiles for future years were calculated by using the load projections for each of the sectors from the NREL Electrification Futures Study[23] (using a "Low Electrification" scenario, which averages the "Reference" case and "Medium" case) and multiplying with their respective normalized load profiles. To create load profiles for the various weather years, the respective normalized weather dependent load profiles are used for the weather dependent loads, while the weather independent load is assumed to remain unaffected.

To maintain consistency with regional forecasts, these forecasts were scaled so that total annual energy consumption and annual peak load is consistent with the load forecasts reported in the utility's 2023 IRP.

Long-term Capacity Expansion (LTCE)

Aurora LTCE

This study used Aurora to perform LTCE on individual weather year scenarios. The LTCE was configured to determine a least-cost portfolio over a 20-year planning horizon (2024-2043). Importantly, the model was configured to optimize the capacity expansion over an 8760-hour chronology. This chronology is essential for capturing the full spectrum of weather volatility and multi-day weather events over the course of the year. 8760-hour chronology can be computationally expensive; therefore, to keep model runtimes tractable, partial resource builds were allowed for modular resources (e.g. renewables, storage). This ensured that the LTCE model could solve within 4-6 hours.

In addition to 8760-hour chronology, the study identified and implemented a number of practices for Aurora LTCE modeling, which are essential for accurately representing multi-day storage:[24]

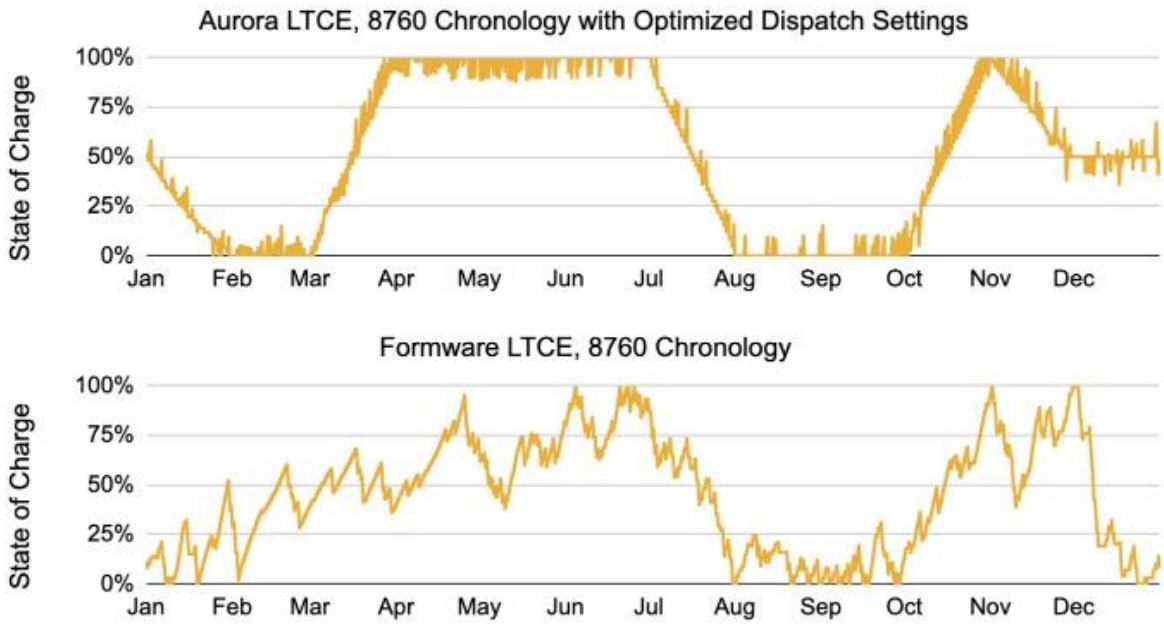
[22] **https://vibrantcleanenergy.com/wp-content/uploads/2020/08/WISdomP-Model_Description(August2020).pdf**

[23] **https://www.nrel.gov/analysis/electrification-futures.html**

[24] Multi-day storage refers to storage technologies with a discharge duration greater than 24 hours, such as 100-hour iron-air batteries

- Within the storage table, the parameter “Optimize Annual Operation” should be set to True. This helps optimize dispatch by recognizing seasonal arbitrage opportunities.
- The “Initial contents” for multi-day storage should be left blank so that the model can optimize the initial and final state of charge over the year (ensuring that initial SOC = final SOC)
- The “shaping method” for storage resources should be set to “price” to ensure least-cost dispatch of storage assets
- Within simulation options, the setting “Use Enhanced Storage Logic” should be turned on
- To achieve higher fidelity modeling of year-round multi-day storage operations, an exogenous dispatch schedule can be entered to guide the dispatch of multi-day storage within Aurora. We implemented this approach for this study. The dispatch schedule for multi-day storage was determined using Formware, which is designed to optimize operations of multi-day storage across all 8760-hours of the year. Figure A2 compares Aurora’s endogenous discharge of multi-day storage against the hourly dispatch schedule optimized by Formware. The Formware dispatch profile is better optimized to shift energy across days, weeks, months, and seasons.

Figure A2: Dispatch of multi-day storage asset within Aurora and Formware LTCE models



Formware

Formware™ is a long-term capacity expansion and production cost model developed by Form Energy. Formware was built to model the dynamics of an evolving grid, such as (a) weather-driven volatility in reliability conditions, and (b) interactions between renewables and storage across daily, weekly, and seasonal time scales. The model is designed to optimize resource investment decisions and production cost simulation within a single step, thus ensuring that resource portfolios are both least-cost and reliable across all 8760 hours of the year.

This study utilized a feature known as multi-scenario co-optimization, in which the model optimizes resource build across multiple scenarios at once to be least-cost, while ensuring load is met across all 8760 hours of each scenario. In this study, the scenarios were used to represent five different weather years. The five weather years were weighted equally within the optimization. The optimization was performed over a 20-year planning horizon, similar to the Aurora LTCE (years 2024-2043). However, to reduce computational runtime, the resource investments were optimized in 5-year batches, rather than modeling each individual investment year.

Production cost modeling

The portfolios resulting from LTCE modeling were run through a production cost simulation on 35 different weather year scenarios. This production cost simulation was used to assess both portfolio cost and reliability. Formware was used to perform the production cost simulation. The model optimizes resource dispatch over an 8760-hour horizon, which is important to both (a) capture full spectrum weather conditions, in chronological order, over the course of the year, and (ii) accurately represent the ability of long-cycle resources, like multi-day storage, to shift energy across weeks, months, and seasons.

The portfolio cost reported by the simulation is inclusive of all capital costs, operational costs, and ITC/PTC tax credits. Capital costs for new resource investments were assumed to be amortized over each resource's useful life. The costs reported in Figures 5 and 7, as well as Appendix B, represent the average cost across all 35 weather year simulations.

Portfolio reliability is reported as expected unserved energy, which is equivalent to the average fraction of annual energy consumption that was unserved (i.e., loss of load) across all 35 weather scenarios.

Appendix B: Supplemental portfolio cost results

This appendix provides the cost breakdown by resource type for portfolios displayed in Figures 5 and 7. Portfolio costs include amortized capital costs (inclusive of ITC) of new resources, annual operating costs of new and existing resources, and annual production tax credits for new and existing resources. It should be noted that the costs displayed for natural gas resources do not include any capital costs associated with the utility's planned coal to gas conversions.

Figure B1: Breakdown of 2038 portfolio costs from Aurora LTCE

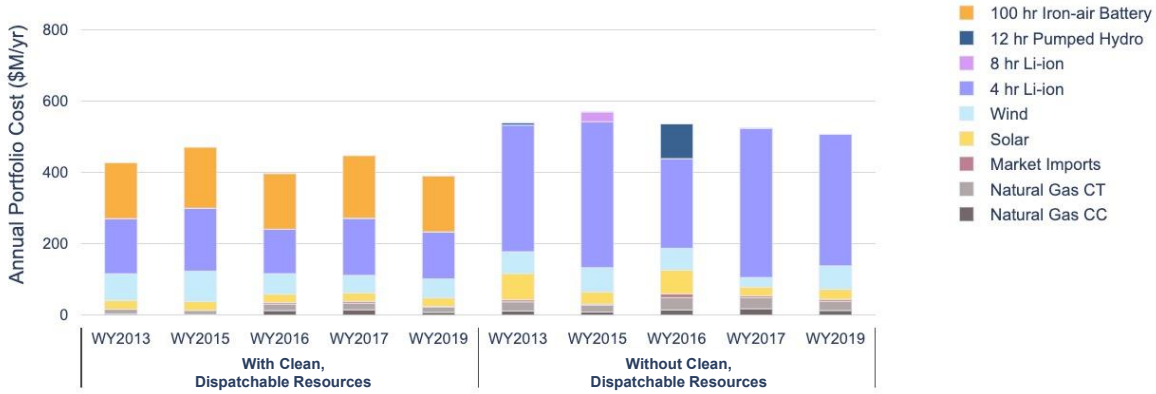
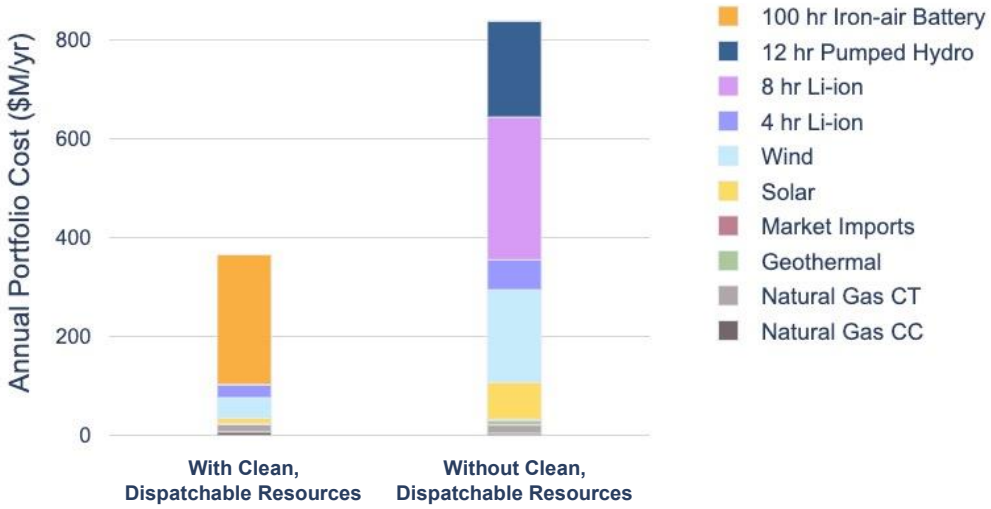


Figure B2: Breakdown of 2038 portfolio costs from Formware multi-weather year co-optimization



Appendix C: Candidate resource assumptions

This appendix provides the cost and technology attributes for each of the candidate resources modeled within this study. All candidate resource assumptions were sourced directly from the supply-side resource table of the utility's last-released IRP, with the exception of green hydrogen.[25] All costs are provided in real 2024 dollars.

Table C1: Candidate resource performance attributes

	General Attributes		Storage Attributes		Renewable Attributes	Thermal Attributes
Candidate Resource	Useful Life (years)	Tax Credits Applied	Duration (hours)	Roundtrip Efficiency (%)	Average Capacity Factor (%)	Heat Rate (btu/kWh)
Wind (Region 1)	30	PTC			35.0%	
Wind (Region 2)	30	PTC			45.0%	
Solar	30	PTC			30.2%	
Geothermal	30	PTC				
4 hr Li-ion	20	ITC	4	85%		
8 hr Li-ion	20	ITC	8	85%		
12 hr Pumped Hydro	75	ITC	12	80%		
100 hr Iron-air Battery	30	ITC (domestic content adder)	100	43%		
SMR	60	PTC				10,461
Green Hydrogen (electrolyzer + underground storage + combustion turbine)	35	45V	500	22%		

[25] Green hydrogen was represented as an energy storage asset – specifically, a combination of a hydrogen electrolyzer, underground storage, and combustion turbine. This was done to more accurately reflect the costs and operations associated with production, storage, and consumption of green hydrogen. This is different from how hydrogen was modeled in the utility's IRP, which represented green hydrogen as a thermal generator with access to readily-available hydrogen fuel.

Figure C1: Candidate resource capex assumptions

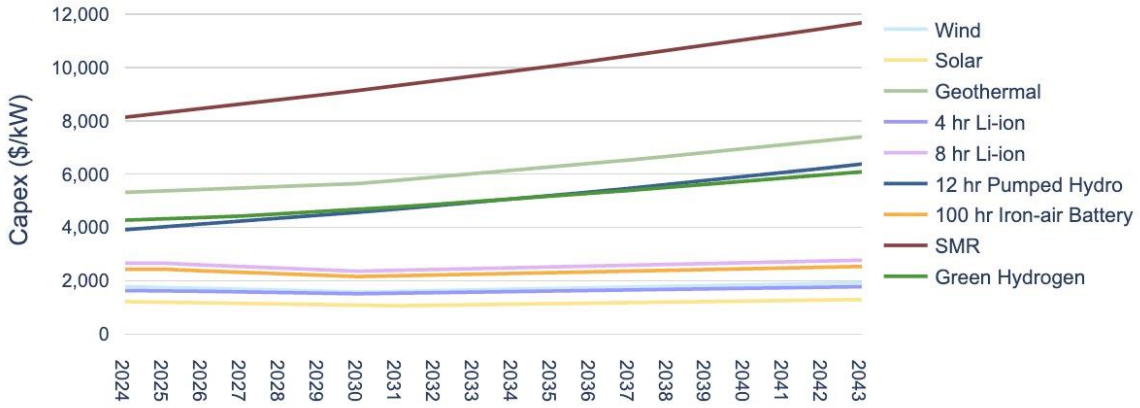


Figure C2: Candidate resource fixed O&M assumptions

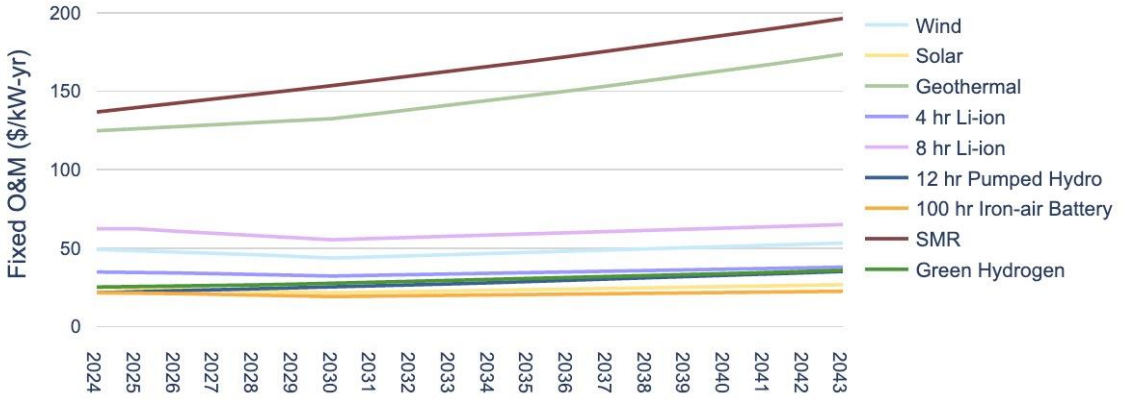
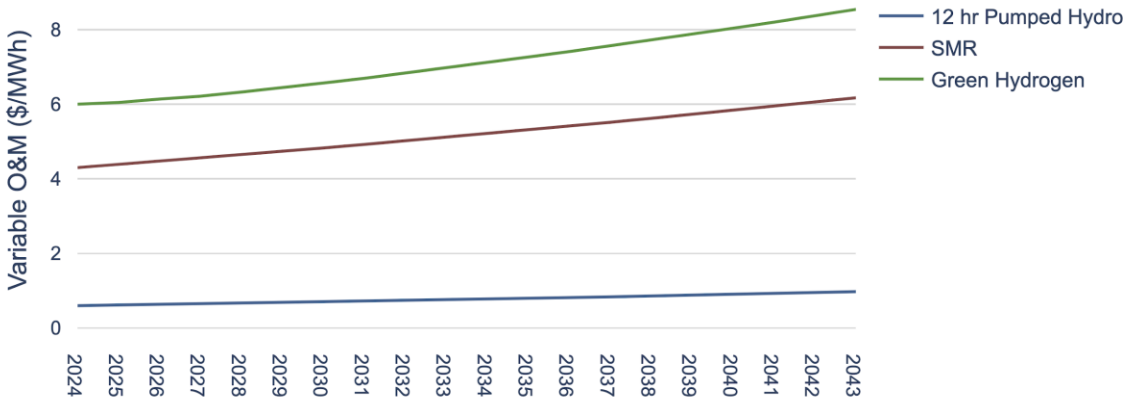



Figure C3: Candidate resource variable O&M assumptions